Discrimination in the Trumpian Politics on People: Evaluated through Sentiment Analysis

Oğulcan Bayol
Professor Srinivas Bangalore

Abstract

Ever since Donald Trump has assumed his position as the president, there has been controversy about whether or not he discriminates against different groups of people. Specifically, debaters tend to take two sides: those who argue that Trump segregates people based on factors such as, but not limited, race, gender, sexual orientation, and national roots, and those who argue against the claims of this group. In this paper, we aim to offer a solution to this controversy by using computational algorithms to evaluate the ways in which Trump approaches different groups of people, and contrast them against each other to decide whether or not there is discrimination. Our approach is to use sentiment analysis algorithms to assign sentiments to Trump's tweets, look for how Trump has used certain keywords positively and negatively across his tweets, and compare these values with each other. Our implementation consists of the sentiment analysis algorithms that are made available, and that we made use of along with Python code that computes the percentages Trump used a user-input keyword positively and negatively in his tweets aligned with their sentiments. Results such as the comparative analysis of how Trump used keywords targeted at different groups of people positively and negatively suggest that Trump does segregate people based on gender, race, religion, sexual orientation, national roots, and multiple other characteristic factors, which offers a solution to the controversy. However, our work still has limitations that call for future work.

1. Introduction

Decades after the abolition of slavery and the passage of Civil Rights Act, President Donald Trump makes remarks that spur debates about whether or not he discriminates against people based on characteristics such as, but not limited to, gender, race, sexual orientation, and national roots.

The controversy is highly polarized. On the one hand, we have Trump's opponents who claim that his claims make, without a doubt, several violations of human rights. On the other hand, we have Trump and his proponents who repeatedly argue against accusations of racism, misogyny, xenophobia, islamophobia, and homophobia by dismissing them and claiming instead that Trump does not segregate anyone based on their characteristics.

During his 2016 presidential campaign, Trump dismissed racism accusations by claiming that he was the "least racist person there ever is." [1]

Also during the course of his campaign, multiple women came forward and accused Trump with misogyny and sexual misconduct. Sarah Sanders, Trump's spokeswoman, was asked about whether or not the president's official explanation was that all accusers, making up at least 17 women, were lying, and Sanders confirmed them. [2] Trump himself also explicitly refuted all allegations. [3]

Trump failed to acknowledge Pride Month and attempted a ban on transgender military service. Because of incidents such as, but not limited to, these, numerous opponents also call him homophobic and transphobic. [4]

After Trump said the US should stop "admitting people from all these shithole countries" meaning immigrants from Haiti and El Salvador, and demanded "taking out" Haitans, his opponents immediately accused him of xenophobia. [5] Later, Trump denied saying anything derogatory about Haitan people, and claimed that the language reported was not the language he used. [6]

These constitute only some of what has been reviving the controversy repeatedly. In this paper, we seek to provide an answer to this controversy through computational algorithms that can mine Trump's attitude towards different groups of people. In other words, we hope to provide data that can serve well for a particular side's argument. We will conclude by evaluating whether or not we have collected such data, and offering suggestions for further work upon our research.

2. Related Work

2.1. Sentiment Analysis Algorithms

Since we had analyzing Trump's language in mind, we have decided to investigate options within natural language processing, an area dedicated to processing large volumes of natural language. Sentiment analysis stood out from various techniques within this field since it has been used popularly to mine opinions in different contexts. Such being the case, we have decided to research algorithms tailored for this technique.

In their paper [7], Medhat, Hassan, and Korashy provide a survey of sentiment analysis algorithms and their applications. This work informed us of Naive Bayes and Support Vector Machines as options that we could take advantage of. Another paper [8] by Gokulakrishnan, Priyanthan, Ragavan, Prsath, and Perera performs sentiment analysis on a set of tweets through algorithms and evaluates the performance of these algorithms by contrasting the computed sentiment values against the actual sentiment values. This work suggested Random Forest in addition what we have already found in the previous paper as an option that we could make use of. In another work [9], Xia, Zong, and Li survey ensemble techniques for sentiment classification. From this source, we learned that the Perceptron algorithm is another option we could use for our analysis.

After learning about these algorithms and their mechanics, we have surveyed sources providing implementations for them. Eventually, we found academic research conducted by Ansari, Seenivasan, Anandan, and Lakshmanan [10] that provides implementations for 10 different sentiment analysis algorithms, and uses their results to contrast their performances against each other. We saved a copy of the directory containing all implementations and files necessary to run them, that was made available to public on GitHub, for our own work.

2.2. Training Corpus

Of course, sentiment analysis algorithms require training data in order to function. This is why the next phase of our research involved looking for training corpus that we could feed into the implementations we had found.

Since we thought that researching papers that performed sentiment analysis on tweets might provide us with the training corpus they used in their work, we have started surveying these works. Gautam, Noel, and Goel's study [11] takes advantage of a tool named SentiNet to compute positivity, negativity, and neutrality scores of tweets collected from a database called sentiment140. After learning about sentiment140, we have researched other sources using this database to see whether or not we would be able to find a work that aligned tweets from this database with their sentiments because the scores in this study were not binary sentiment values. Eventually, we found that in their work, Sanders Analytics aligned tweets from sentiment140 with their corresponding sentiments through computational processing. [12]

2.3. Analysis Corpus

Last, we needed some source that would easily provide us with Trump's remarks. Since using tools to scrape information from news articles would take a lot of time, and make the implementation of our work much more complicated, we decided to use a source that provides a bare collection of Trump's remarks. This immediately brought out Twitter since Twitter is a social media platform which everyone uses to reflect a collection of their opinions and remarks. Such being the case, we decided to collect Trump's tweets for our work.

Soon after, we have found Trump Twitter Archive [13], and exported all tweets Trump himself has ever posted ever since he created his Twitter account until April 23, 2018 to a CSV file.

3. Approach

In light of our research we consider the following approach to be the most effective:

3.1. Use Sentiment Analysis Algorithms to Analyze Tweets' Sentiments

Our survey shows that sentiment analysis algorithms can be exploited to analyze the sentiments in remarks. If we want to understand Trump's sentiments about different groups of people, we need to, first, use these algorithms to compute the sentiments in his remarks. Given that we selected

Trump's tweets as a group of texts representative of Trump's remarks, we will use sentiment analysis algorithms to analyze the sentiments in Trump's tweets.

3.2. Compute Positive and Negative Use Proportions of Keywords Across Analyzed Tweets

A comparative analysis of the positive use and negative use proportions of different keywords and phrases across Trump's tweets would give insight into how Trump approaches different groups of people. This implies that: first, we need to write code that iterates over all of Trump's tweets aligned with their sentiments by sentiment analysis algorithms to find positive use and negative use proportions for user-input keywords and phrases; second, we need to compare the proportions for different keywords and phrases to assess whether or not his politics on people are discriminatory.

4. Implementation

To implement the aforementioned approach, we have taken four main steps:

4.1. Preprocess Training Corpus

Since the sentiment analysis algorithms we would use would need filtered training corpus to function, we preprocessed the training corpus we mentioned in our related work through *preprocess.py*, the preprocessing tool Ansari, Seenivasan, Anandan, and Lakshmanan provides in their GitHub release for their academic work.

4.2. Train Sentiment Analysis Algorithms on Preprocessed Training Corpus

After we finished preprocessing training corpus, among the implementations we have found online, we picked those for the Random Forest algorithm, Support Vector Machines, and Multi-Layer Perceptron. Then, we trained these implementations on the preprocessed training corpus mentioned in the previous section.

4.3. Perform Sentiment Analysis on Preprocessed Analysis Corpus

After training, the sentiment analysis implementations we have selected were ready to perform sentiment analysis. However, the analysis corpus, which is the collection of Trump's tweets, was not ready since it needed to be preprocessed first, which was what we did next by running *preprocess.py* from Ansari, Seenivasan, Anandan, and Lakshmanan's GitHub release on the raw analysis corpus. Next, we ran *randomforest.py*, *svm.py*, and *neuralnet.py* from the same source, which refer to implementations of Random Forests, SVM, and Multi-Layer Perceptron respectively, on the preprocessed analysis corpus in order to perform sentiment analysis on Trump's tweets through three different sentiment analysis algorithms. The results were stored in *randomforest.csv*, *svm.csv*, and *1layerneuralnet.csv*.

4.4. Write Code that Computes Positive Use and Negative Use Percentages

The last step of the implementation was to write code that iterates over Trump's tweets and sentiment results output by the aforementioned sentiment analysis algorithms to compute the percentages Trump used a user-input phrase and keyword positively and negatively. For this purpose, we have coded *analyze.py*, which is shown below:

```python
import sys
with open("results/randomforest.csv") as rf:
    rfLines = rf.readlines()

with open("results/svm.csv") as svm:
    svmLines = svm.readlines()

with open("results/1layerneuralnet.csv") as nn:
    nnLines = nn.readlines()

with open("trumptweets.txt") as tweets:
    tweetLines = tweets.readlines()

while True:
    phrase = raw_input("Enter phrase to look for: ")

    rfPos, rfNeg, svmPos, svmNeg, nnPos, nnNeg = 0

    for i in range(len(tweetLines)):
        if phrase in tweetLines[i]:
            if int(rfLines[i].split(",")[1]) == 1:
                rfPos = rfPos + 1
            else:
                rfNeg = rfNeg + 1

            if int(svmLines[i].split(",")[1]) == 1:
                svmPos = svmPos + 1
            else:
                svmNeg = svmNeg + 1

            if int(nnLines[i].split(",")[1]) == 1:
                nnPos = nnPos + 1
            else:
                nnNeg = nnNeg + 1

    print("Random Forest : " + str((float(rfPos)/float(rfPos + rfNeg))*100) + "% " + "Positive, " +
        str((float(rfNeg)/float(rfPos + rfNeg))*100) + "% Negative")
    print("SVM: " + str((float(svmPos)/float(svmPos + svmNeg))*100) + "% " + "Positive, " +
        str((float(svmNeg)/float(svmPos + svmNeg))*100) + "% Negative")
    print("Multi-Layer Perceptron: " + str((float(nnPos)/float(nnPos + nnNeg))*100) + "% " + "Positive, " +
        str((float(nnNeg)/float(nnPos + nnNeg))*100) + "% Negative")
    print
```

Figure 1: The full implementation of *analyze.py*

5. Results

We have decided to search keywords and phrases under six main characteristics. These are the characteristics that distinguish the groups of people opponents claim Trump discriminates against: gender, sexuality, race, international roots, immigration, and religion.

5.1. Gender

The first controversial characteristic is gender. Opponents claim that Trump discriminates against women while proponents dismiss this claim. Bearing this in mind, in order to collect data around this characteristic, I created three groups of keywords that differentiated women from men. The first group is woman/women versus man/men. The second group is Mrs./Ms. versus Mr./Mister. The third group is Girl/Girls versus Boy/Boys. The positive use and negative use proportions for how Trump used these keywords, as computed by *analyze.py*, is displayed below. P stands for positive use, N stands for negative use, RF stands for Random Forests, SVM stands for Support Vector Machines, and ML stands for Multi-Layer:

Keyword/Phrase	RF	SVM	ML Perceptron	Average
Woman/Women	66% P, 34% N	77% P, 23% N	65% P, 35% N	69% P, 31% N
Man/Men	70% P, 30% N	77% P, 23% N	68% P, 32% N	72% P, 28% N
Mrs./Ms.	77% P, 23% N	65% P, 35% N	62% P, 38% N	68% P, 32% N
Mr./Mister	72% P, 28% N	76% P, 24% N	72% P, 28% N	73% P, 27% N
Girl/Girls	37% P, 63% N	52% P, 48% N	42% P, 58% N	44% P, 56% N
Boy/Boys	62% P, 38% N	75% P, 25% N	61% P, 39% N	66% P, 34% N

Table 1: Trump's Sentiment Statistics for Gender Keywords and Phrases, as Computed by *analyze.py*

The first thing that stands out from these data is that there is a slight difference between average positive use for man/men, 72%, and average positive use for woman/women, 69%. It's 3%. A similar observation can be made when proportions for the keywords in the second group are compared: 73% average positive use for Mr./Mister, and 68% average positive use for woman/women. The difference here is 5%. Although these mathematically demonstrate that there is some difference between the percentage of times Trump approaches men negatively and the percentage of times he approaches women negatively, proponents can easily argue that the difference is not statistically significant, and that it should be dismissed. After all, today, there are more issues tied with women, and Trump might have been addressing those in his tweets, and this might very well explain the slight difference in his positive use proportion for men and his positive use proportion for women. This argument can be granted for the first two groups. However, it does not work against statistics we have gathered for keywords in the third group. Trump's negative use proportion for Girl/Girls is 56% while his negative use proportion for Boy/Boys is 34%. This corresponds to a 22% difference, which looks far from being slight and statistically insignificant. Granted that the last difference is statistically significant, and that a statistically significant difference cannot be attributed to simply addressing women's issues, there is a difference between how Trump approaches men within a specific age range versus how he approaches women within the same age range, which, along with difference data for the first two groups, implies that overall, Trump discriminates against women. These all together support the opponents' argument.

5.2. Sexuality

The second contentious characteristic is sexuality. Opponents argue that Trump discriminates against LGBT people, or people who identify with an orientation other than heterosexual. Considering this, we have collected sexual orientation terms from [14], and computed positive and negative use statistics for them. Further, in order to be able to make a comparative analysis, like the one we have done for gender, we have decided to contrast Trump's use proportions for 'marriage' in general and 'gay marriage'. We demonstrate all statistics we have collected under this characteristic below:

Keyword/Phrase	RF	SVM	ML Perceptron	Average
LGBT/Gay	28% P, 72% N	25% P, 75% N	25% P, 75% N	26% P, 74% N
Marriage	33% P, 67% N	33% P, 67% N	33% P, 67% N	33% P, 67% N
Gay Marriage	0% P, 100% N	0% P, 100% N	0% P, 100% N	0% P, 100% N

Table 2: Trump's Sentiment Statistics for Sexuality Keywords and Phrases, as Computed by *analyze.py*

The 26% average positive use and 74% average negative use statistic for LGBT/Gay stands out. This statistic implies that Trump uses LGBT and Gay predominantly in negative remarks. Although this is suggestive of unfair treatment and discrimination, the proponents, fairly enough, might object and argue that this statistic does not mean anything since there are issues tied with the LGBT community, and that Trump might have, very well, been talking about those, which in turn explains the much greater negative use percentage. However, this is implausible. If Trump had been addressing issues tied with people who identify with an orientation other than heterosexual, he would have also addressed potential solutions and ideal conditions that would arise as a result of those solutions, which would have most likely had positive sentiments associated with them. The sentiments of the two groups of statements would have, then, balanced each other out for the most part, and we would have seen results close to the 50%, 50% benchmark since this benchmark represents a purely balanced/neutral ratio of proportions. However, this is not the case. The 26%, 74% proportion ratio is statistically far from the 50%, 50% benchmark, which in turn falsifies the proponents' argument. In addition to this statistic, Trump uses the keyword marriage positively 33% of the time, on average, while he uses the phrase 'gay marriage' positively 0% of the time, on average. The difference is large, and suggests that Trump is more likely to make a negative comment given that marriage is between people of the same gender. To explain the difference, proponents might run a similar argument based on Trump potentially addressing issues related to gay marriage. However, this argument does not hold because Trump would have addressed solutions and ideal conditions resulting from those solutions in that case, but he never used 'gay marriage' positively, according to all three sentiment analysis algorithms. Such being the case, Trump discriminates against gay people, which proves opponents right.

5.3. Race and Ethnicity

Race and ethnicity are two other characteristics that cause the debate. Because opponents raise most of their charges based on their observations of how Black people are treated, we have decided to concentrate specifically on keywords and phrases that characterize people into this group. In order to determine how we would proceed to collect data under the ethnicity characteristic, we have researched ethnicity categories, and found out that the most common approach characterizes people into either Hispanic or not Hispanic. Having noted all of these, we have collected the following data:

Keyword/Phrase	RF	SVM	ML Perceptron	Average
American/Americans	57% P, 43% N	71% P, 29% N	59% P, 41% N	62% P, 38% N
African American/African Americans/black	39% P, 61% N	64% P, 36% N	44% P, 56% N	49% P, 51% N
Hispanic	58% P, 42% N	50% P, 50% N	50% P, 50% N	52% P, 48% N

Table 3: Trump's Sentiment Statistics for Race and Ethnicity Keywords and Phrases, as Computed by *analyze.py*

On average, when Trump mentions American/Americans, there is 62% probability that his remark is positive. To the contrary, on average, if the remark contains the keyword black, or if American/Americans is preceded by African, the probability that the remark is positive drops down to 49%. At 52%, the probability that a remark containing the keyword Hispanic is positive is much smaller, too. Proponents could run an argument based on having more negative remarks as a result of addressing black people and Hispanic people's issues. However, in order to construct that argument, they need to first show that the differences are statistically insignificant, and use this finding as a premise. However, the differences are 13% and 10%, and do not look statistically insignificant. Unless proponents use statistical methods to prove that these large differences are statistically insignificant, they cannot argue that Trump does not discriminate against people based on race and ethnicity. These all together support the opponents' argument.

5.4. International Roots

International Roots is a characteristic that needs more detailing than other characteristics on this paper. Many opponents argue that Trump discriminates specifically against Middle Easterns. They base their argument on their observations that there are discrepancies between how Trump approaches people from Europen countries and how he approaches people from the Middle East. Keeping this in mind, we have first looked into statistics for the keywords Europe and Middle East. Then, we have created a sample of European countries: Britain, France, and Germany. People from these countries are generally referred to using the keywords British, French, and German. We have collected statistics for how Trump used these keywords. Afterwards, we have created a sample of Middle Eastern countries: Syria, Iran, and Iraq. Next, we have looked at how Trump used Syrian, Iranian, and Iraqi, the keywords used to refer to people from these countries. All results we have collected are shown below:

Keyword/Phrase	RF	SVM	ML Perceptron	Average
Europe	56% P, 44% N	74% P, 26% N	54% P, 46% N	61% P, 39% N
Middle East	35% P, 65% N	68% P, 32% N	42% P, 58% N	48% P, 52% N
British/French/German	52% P, 48% N	72% P, 28% N	55% P, 45% N	60% P, 40% N
Iraqi/Iranian/Syrian	41% P, 59% N	45% P, 55% N	31% P, 69% N	39% P, 61% N

Table 4: Trump's Sentiment Statistics for International Roots Keywords and Phrases, as Computed by *analyze.py*

First, the positive use proportion for Europe is, on average, 61% while the positive use proportion for Middle East is, on average, 48%. Once again, 13% difference does not look statistically insignificant, and proponents cannot run an argument based on having more negative remarks as a result of addressing issues related to the Middle East unless they use statistical techniques to prove that the difference is statistically insignificant. But proponents can argue that these are terms that are not used to describe people but countries, and such being the case, they do not mean anything about how Trump approaches people from these countries. This is where the second set of data comes into play. The 60% average positive use proportion for British/French/German versus the 39% average positive use proportion for Iraqi/Iranian/Syrian implies a 21% difference between how Trump approaches European people versus how he approaches Middle Eastern people. This difference is quite large, and it's most likely statistically significant. Further, these terms are actually used to refer to people. Unless proponents prove that this large difference is statistically insignificant, they cannot claim that Trump does not discriminate against Middle Eastern people. These all together support the opponents' argument.

5.5. Immigration

Opponents also claim that immigrants are not welcome in Trump's America, and that Trump discriminates against them. To collect data under this characteristic, we have collected various terms related to immigration. Upon using *analyze.py* on these terms, we have found out that Trump used a number of them. Specifically, he used alien, refugee, deport, visa, and words starting with immig. After collecting sentiment data for deport and visa, we have merged all sentiment data for alien, refugee, and immig by weighting their sentiment data by the number of their occurrences and adding them up. In addition, considering that many Mexicans are targeted in Trump's immigration remarks, we have collected sentiment data for the keyword Mexican. All shown below:

Keyword/Phrase	RF	SVM	ML Perceptron	Average
Immig/Alien/Refugee	51% P, 49% N	57% P, 43% N	41% P, 59% N	50% P, 50% N
Deport	80% P, 20% N	100% P, 0% N	70% P, 30% N	83% P, 17% N
Visa	25% P, 75% N	50% P, 50% N	25% P, 75% N	33% P, 67% N
Mexican	29% P, 71% N	49% P, 51% N	31% P, 69% N	39% P, 61% N

Table 5: Trump's Sentiment Statistics for Immigration Keywords and Phrases, as Computed by *analyze.py*

At first, one might conclude that Trump is neutral and impartial towards immigrants, refugees, and aliens because the positive use proportion versus the negative use proportion stands right at 50% P, 50% N, which suggests neither a negative approach nor a positive one. However, the next two pieces of data suggest that this is not true. The first piece suggests that Trump looks on deporting people mostly favorably, 80% positive use versus 50% negative use. The second piece shows that Trump uses the keyword visa mostly negatively, 33% positive use versus 67% negative use, which is consistent with what the first piece suggests because someone who looks on deporting favorably would plausibly look on visas, which allow entry into the United States, negatively. 33% is 17% away from the 50%, 50% benchmark, which represents a completely neutral approach. 80% is 30% away from the same benchmark. These are most likely statistically significant, and unless proponents prove otherwise, they suggest that Trump discriminates against immigrants. The last piece of data is also of no help to the proponents. It suggests that Trump uses the keyword Mexican positively 39% of the time and negatively 61% of the time. Recall Trump's rate for British/French/German, which stands at 60% positive use and 40% negative use. The 21% difference is most likely statistically significant, and unless proponents show otherwise, they cannot argue that Trump is simply addressing issues tied to Mexicans, and that's why his remarks about Mexicans are more likely to be negative. Such being the case, this piece of evidence, too, suggests that Trump discriminates against immigrants.

5.6. Religion

Last, many discrimination charges are raised against Trump based on religion. Opponents think that Trump discriminates against Muslims. Accordingly, we have collected sentiment data for Jew, Christian, and Muslim/Islam to be able to make a comparative analysis. We have collected the following data:

Keyword/Phrase	RF	SVM	ML Perceptron	Average
Jew	84% P, 16% N	88% P, 12% N	33% P, 67% N	68% P, 32% N
Christian	46% P, 54% N	57% P, 43% N	49% P, 51% N	51% P, 49% N
Muslim/Islam	36% P, 64% N	56% P, 44% N	44% P, 56% N	45% P, 55% N

Table 6: Trump's Sentiment Statistics for Religion Keywords and Phrases, as Computed by *analyze.py*

Trump's average negative use of Jew is 32% while his average negative use of Christian is 49%.

This means that there's a 17% difference between the two. In comparison, when we contrast his average positive use of Jew against his average positive use of Muslim/Islam, we observe an even larger difference, 23%. These large differences are most likely statistically significant. Proponents might construct a counter-argument: Trump makes more negative remarks because he addresses issues around Christianity and Islam, and that does not mean anything about his attitude towards Muslims or Christians. However, that counter-argument requires the premise that the differences are statistically insignificant. Unless proponents prove that the differences are indeed significantly insignificant, which looks unlikely given the values of these differences, the data suggest that Trump discriminates against not only Muslims but also Christians.

6. Conclusion

This paper first addresses the problem that there is controversy about whether or not Donald Trump discriminates against people based on characteristics such as gender, sexuality, race/ethnicity, national roots, immigration, and religion. Next, it highlights its aim to offer a solution to this controversy by using computational tools and algorithms to extract data that support the argument of one of the sides. Subsequently, it proposes a solution: use different sentiment analysis algorithms to assign sentiments to all tweets Trump has ever posted, write code that computes positive use and negative use percentages for user-input keywords and phrases iterating over Trump's tweets aligned with their sentiments, use this code to collect Trump's sentiment proportions for keywords and phrases under these characteristics, and compare these proportions to evaluate whether or not Trump discriminates against people based on the aforementioned characteristics. Although we have not used statistical techniques to evaluate whether or not the differences in positive use and negative use proportions for different keywords and phrases are significant, most of them are large enough to suggest that it's unlikely they are statistically insignificant. Unless Trump and his proponents use such techniques to show that these large differences are indeed statistically insignificant, and use this finding as a premise in constructing the counter-argument that Trump makes more negative remarks towards people in these groups only because he addresses issues related to them, these data support the opponents' claims and suggest that Trump does indeed discriminate people based on gender, sexuality, race/ethnicity, national roots, immigration, and religion. This in turn means that the study has reached its goal by providing the opponents with data that support their argument.

Although our study has reached its goal, it has limitations that call for future work. One of its limitations was its time period. It did not allow us to use various other sentiment analysis algorithms on Trump's tweets. Many other sentiment analysis algorithms that could have been incorporated into our study include Naive Bayes, Maximum Entropy, XGBoost, Recurrent Neural Networks, and Convolutional Neural Networks. It is essential to exploit more algorithms because our method relies on averaging sentiment data from different sentiment algorithms, and increasing the number of sentiment analysis algorithms we use means getting more accurate average sentiment proportion results. We encourage people who want to add onto our work to consider this.

Limited time also did not allow us to use statistical techniques to show that the differences we have observed are statistically significant. We have relied heavily on observing large differences in concluding that they are most likely statistically significant. However, we need more work that leverages such techniques to provide a solid mathematical basis for the significance of the differences. We ask people who want to conduct future research to bear this in mind.

Another limitation of our study was that it only used Trump's tweets. Although we think Trump's tweets are representative enough in that they contain Trump's remarks about pretty much any topic, people who want to add onto our work might want to scrape Trump's remarks from other sources, and combine them with his tweets before performing any sentiment analysis. This method can yield an even more representative set of Trump's remarks. One other source to scrape more remarks is transcripts of Trump's speeches. However, adding remarks from this source might cause problems since Trump and his proponents can claim that those were not written by Trump himself and might have been easily manipulated. We ask people who would like work around this limitation to carefully assess these considerations.

Last, this work does not take advantage of various other linguistic approaches that can be used to evaluate whether or not there is discrimination. One of these approaches is using a parser, collecting parse data for different keywords and phrases under the characteristics outlined in this study, and contrasting gathered data against each other to evaluate.

7. Ethics

This paper represents my own work in accordance with University regulations.

Oğulcan Bayol

References

[1] E. Scott. "Donald Trump: I'm 'the Least Racist Person'." *CNN*, 15 Sept. 2016, https://cnn.it/2rFbL2Q.

[2] E. Ponsot and S. Slobin. "Donald Trump: I'm 'the Least Racist Person'." *Quartz*, 17 Nov. 2017, qz.com/1130324/17-women-have-accused-donald-trump-of-sexual-assault-or-misconduct-its-time-to-revisit-those-stories/.

[3] M. Kelly. "President Trump and Accusations of Sexual Misconduct: The Complete List." *The Washington Post*, 22 Nov. 2017, https://wapo.st/2rGrtun.

[4] G. Lopez. "Trump's First Year Was Awful for LGBTQ Rights." *Vox*, 22 Jan. 2018, https://bit.ly/2IGr3if.

[5] J. Dawsey. "Trump Derides Protections for Immigrants from 'Shithole' Countries." *The Washington Post*, 12 Jan. 2018, https://wapo.st/2wDBm1X.

[6] D. Scott. ""Shithole" Countries, Donald Trump's Latest Racist Tirade, Explained." *Vox*, 12 Jan. 2018, www.vox.com/policy-and-politics/2018/1/12/16882840/donald-trump-shithole-daca.

[7] W. Medhat, A. Hassan, and H. Korashy. "Sentiment Analysis Algorithms and Applications: A Survey." *Ain Shams Engineering Journal*, vol. 5, no. 4, 2014, pp. 1093-1113., doi:10.1016/j.asej.2014.04.011.

[8] B. Gokulakrishnan, P. Priyanthan, T. Ragavan, N. Nadarajah, and A. Perera. "Opinion Mining and Sentiment Analysis on a Twitter Data Stream." *International Conference on Advances in ICT for Emerging Regions (ICTer2012)*, 2012, doi:10.1109/icter.2012.6423033.

[9] R. Xia, C. Zong, and S. Li. "Ensemble of Feature Sets and Classification Algorithms for Sentiment Classification." *Information Sciences*, vol. 181, no. 6, 2011, pp. 1138-1152., doi:10.1016/j.ins.2010.11.023.

[10] A. F. Ansari, A. Seenivasan, A. Anandan, and R. Lakshmanan. "Twitter Sentiment Analysis." 12 Nov. 2017, github.com/abdulfatir/twitter-sentiment-analysis/blob/master/docs/report.pdf

[11] A. Goel, J. Gautam, and S. Kumar. "Real Time Sentiment Analysis of Tweets Using Naive Bayes." *2016 2nd International Conference on Next Generation Computing Technologies (NGCT)*, 2016, pp. 257-261., doi:10.1109/ngct.2016.7877424.

[12] N. J. Sanders. " Twitter Sentiment Corpus." in *Sanders Analytics*. Sanders Analytics LLC., 2013.

[13] "Trump Twitter Archive." *Trump Twitter Archive*, 23 Apr. 2018, http://www.trumptwitterarchive.com/archive.

[14] E. R. Green and E. Peterson. "Gender & Sexuality Terminology." Aug. 2015, lgbt.williams.edu/resources/terms/.